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Understanding the order effect of online review sentiments and product features

Extended Abstract

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1. Introduction

Online reviews have played an increasingly important role in the popularity and success of e-commerce (Yin et al. 2014). The decreasing digital divide and ubiquitous internet access, along with the proliferation of smart mobile devices, has resulted in an exponential increase in the online purchase of goods and services. Additionally, customers are encouraged and incentivized to share their personal experience using the product or service. Such experiences represented on internet platforms are captured through electronic word-of-mouth, typically in the form of online reviews. Prior studies on online reviews have shown that the experience of consumers plays an important role as an information source when potential consumers make purchasing decisions (Luo et al. 2013). Researchers have also revealed that opinion mining and sentiment analysis of online reviews can be used to predict the pricing power (Archak et al. 2011) and sales (Chevalier and Mayzlin 2006; Gu et al. 2012) of the product.

Studies on online reviews and their sentiments have primarily focused on its economic outcomes by predicting sales, brand performance measures, or stocks. Prior studies have shown that each review is distinct on its own and may mention various levels of product features as per the reviewer's discretion (Zhou and Guo 2017). Studies have also shown the declining trend in review valence (ratings) and review volume over time and sequence (Godes and Silva 2012; Li and Hitt 2008; Moe et al. 2011; Moon et al. 2010; Wu and Huberman 2008). Such trends were observed in ratings, review volume, helpfulness and not the information that could be extracted from the textual content of a review.

Our study attempts to fill the gap in the evolution of online review sentiments and product features extracted from the review text. We leverage the theoretical framework of expectation-confirmation theory and motivation theory to understand the relationship between the review sentiments as well as the number of product features over the review order. The order of a review represents the sequence of reviews in terms of posting time. We found that the review order had a negative relationship with the overall sentiments and the number of product features present in the textual content of a review for a given product. Additionally, the negative relationship between review order and overall sentiments of a review is weaker when the number of product features present is high. The findings of this study provide a new perspective for practitioners to give higher emphasis to features present in product reviews and sentiments observed in initial product reviews. This study contributes to the literature of online reviews while focusing on the order effect on the textual content of reviews.

2. Theoretical background

Expectation-confirmation theory is a cognitive theory that aims to explain consumer's post-purchase satisfaction of a product (Oliver 1980). The theory posits that the discrepancy (i.e., positive or negative disconfirmation) between consumers' expectations and perceived performance will influence post-purchase satisfaction. Before purchasing a product, consumers can observe the existing reviews of the

product. The sentiments associated with prior reviews shape the consumers' expectations of the product performance. After purchasing the product, consumer's satisfaction or dissatisfaction could be reflected in the sentiments associated with subsequent reviews of the product. A lower-order review represents the prior reviews posted for a product and encapsulates the consumers' expectation of a product. A higher-order review reflects more recent reviews and these reviews could show dissatisfaction due to a mismatch between the expected and perceived performance. So, as the order of the review increases, the dissatisfaction from consumers increases.

Furthermore, consumers who spend time and effort to write product reviews often hope that their reviews can exert some influence on others' purchase decisions (Mudambi and Schuff 2010). A motivational theory by Wu & Huberman (2008) explains the decision-making process from a potential reviewers' perspective. Based on this theory, the cost or effort of writing a review depends on the amount of influence the review will have on future buyers. We apply this motivation theory to explain the trend in the number of product features present in an online review text. If a product's existing reviews have mentioned a higher number of product features, then future consumers may be less motivated to post a similar experience on the product features as the efforts to write a repetitive review might not influence prospective customers. To perceive a higher impact on his review, the consumer will try to post some unique features or experience which is not present in prior reviews. So, a lower-order review will mention a higher number of product features as the experience of customers could be more unique. Conversely, a higher-order review will mention fewer product features as the customers will have less unique content to write.

Compounding the effect of the number of product features on the dynamics of review sentiments, we analyze the moderating role of the number of product features on the negative trend of review sentiments. A study by Ma et al. (2013) empirically demonstrates that reviewers providing longer reviews (more product features) tend to rely less on prior reviews when contributing their personal opinion on a given product. The expectation of product performance set by prior reviews is closer to the actual product performance captured in a longer review which yields a weaker negative relationship between review order and sentiments. Conversely, fewer product features are discussed in shorter reviews relying more on prior reviews. So, the expectation of product performance set by prior reviews is farther from the actual product performance, resulting in higher dissatisfaction. This would lead to a stronger negative relationship between the sentiments associated with a review and the review order.

3. Data & Methodology

We collaborated with a Fortune 500 company that manufactures consumer products in the garment industry for our analysis. The company made all the reviews for its products sold on Amazon.com available for the researchers. Customers' post-purchase behavior is reflected through product reviews and ratings on the product webpage visited by potential customers of that product. The company provided around 257k reviews for 50 popular products starting from 2006 to 2017. For each review, the following data were collected: star rating, review text and date of the review.

The variable *order* was operationalized by ordering the reviews for a given product by the review date. We measured the sentiments of the review text by using a lexicon and rule-based sentiment analysis tool VADER (Valence Aware Dictionary and sEntiment Reasoner) (Hutto and Gilbert 2014). We operationalized the number of product features using the variable *numfeat*, which is the total number of product features present in a review. We adopted the noun-phrase extraction method suggested by Hu and Liu (2004) to determine the product features from the review text. To analyze the moderating effect of the number of product features, we operationalized a categorical variable *numfeat_cat*, where the value is 1 when the number of product features is more than 2 and 0 otherwise. Review length was measured by the total number of words in a review (Mudambi and Schuff 2010). We also included product-level fixed effects to control for any dynamic trend observed at the product level as suggested by Godes & Silva (2012).

The product feature generation process at the review level is modeled as a function of review order, associated rating and length of the review, while controlling for product fixed effects and year level effects. The variable *numfeat* is a discrete variable, which could be best estimated by using Poisson regression. The sentiments generation process at the review level is modeled as a function of review order, associated review length, the number of product features and the *order-numfeat* interaction term while controlling for product fixed effect and year level effects. The sentiments model is estimated by using OLS regression.

4. Results

The coefficients of order variable in both *sentiments* and *numfeat* models are negative and significant. This indicates that the sentiments associated with a review will negatively relate to the review order for a given product and the number of product features associated with a review will have a negative relationship with the review order for a given product. The coefficient for the interaction between *order* and *numfeat* is positively significant. By plotting an interaction plot, we found that review order has a negative effect on review sentiments when the number of product features is lower; but this negative effect is weakened when the review has a higher number of product features.

We also inspected the potential presence of multicollinearity among the variables by estimating the Variance Inflation Factor (VIF) scores. The VIF values were inspected for all the variables under study and all VIF values were less than the threshold of 10, confirming that multicollinearity is not an issue. A log-likelihood ratio test was also performed to assess the importance of order effect on sentiments and level of product features. The significant chi-square values test statistic shows that the addition of *order* variable improves the sentiment and product feature models.

5. Discussion

In this study, we attempt to understand how the order of a review will impact the number of product features and sentiments expressed in the same review for a given product and identify the conditions under which the effect of review order on review sentiments will be strengthened or weakened. We propose a theoretical framework supported by expectation-confirmation theory and motivation theory and test it with 257k product reviews collected from Amazon.com. The findings indicate that the intensity of sentiments and the number of product features negatively relate to the review order for a given product. The number of product features also moderates the relationship between sentiments and review order. Specifically, the negative effect of review order on review sentiments is weaker (stronger) when more (fewer) product features are mentioned in a review.

This study makes several contributions to the literature of online reviews. First, this study contributes to a better understanding of the evolution of sentiments and product features in an online review. This study is designed to answer how prior review sentiments impact future review sentiments and how the quantity of product features is posted on online reviews varies with the review order for a given product. The results suggest a negative relationship between the review order and review sentiments. Furthermore, this negative relationship is weaker when the product review contains more product features and vice versa. Second, this study also understands the motivation behind customers on mentioning product features in online reviews. We found that if prior reviews for a given product have a higher number of product features, then subsequent reviewers will be reluctant to mention a higher number of features in their reviews as they believe that their review will have a lower impact on prospective customers.

This study has several important implications for online retailers and product managers. One implication for online retailers is that they could focus more efforts on the highlighting or focusing initial reviews for newly launched products or recently updated products. Another implication for managers is to sort out reviews by the number of product features posted for both positive and negative experiences which ease decision making for prospective customers.

This study has several limitations that need to be addressed in future studies. First, the method of sentiment extraction is highly dependent on the lexicon/dictionary it is based on. There are several other sophisticated natural language processing methods to extract product features from online reviews. Second, as is the case for many prior studies on online reviews, this study has focused exclusively on data from one industry, i.e. garment. Theoretically, the hypothesis could be applied to other tangible products like books, mobile phones, laptops, etc. Future research could be extended by considering the effect of product type or comparing across product categories and the corresponding sentiment dynamics. Furthermore, the moderating effect of gender, product category, external eWOM could yield interesting results.

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